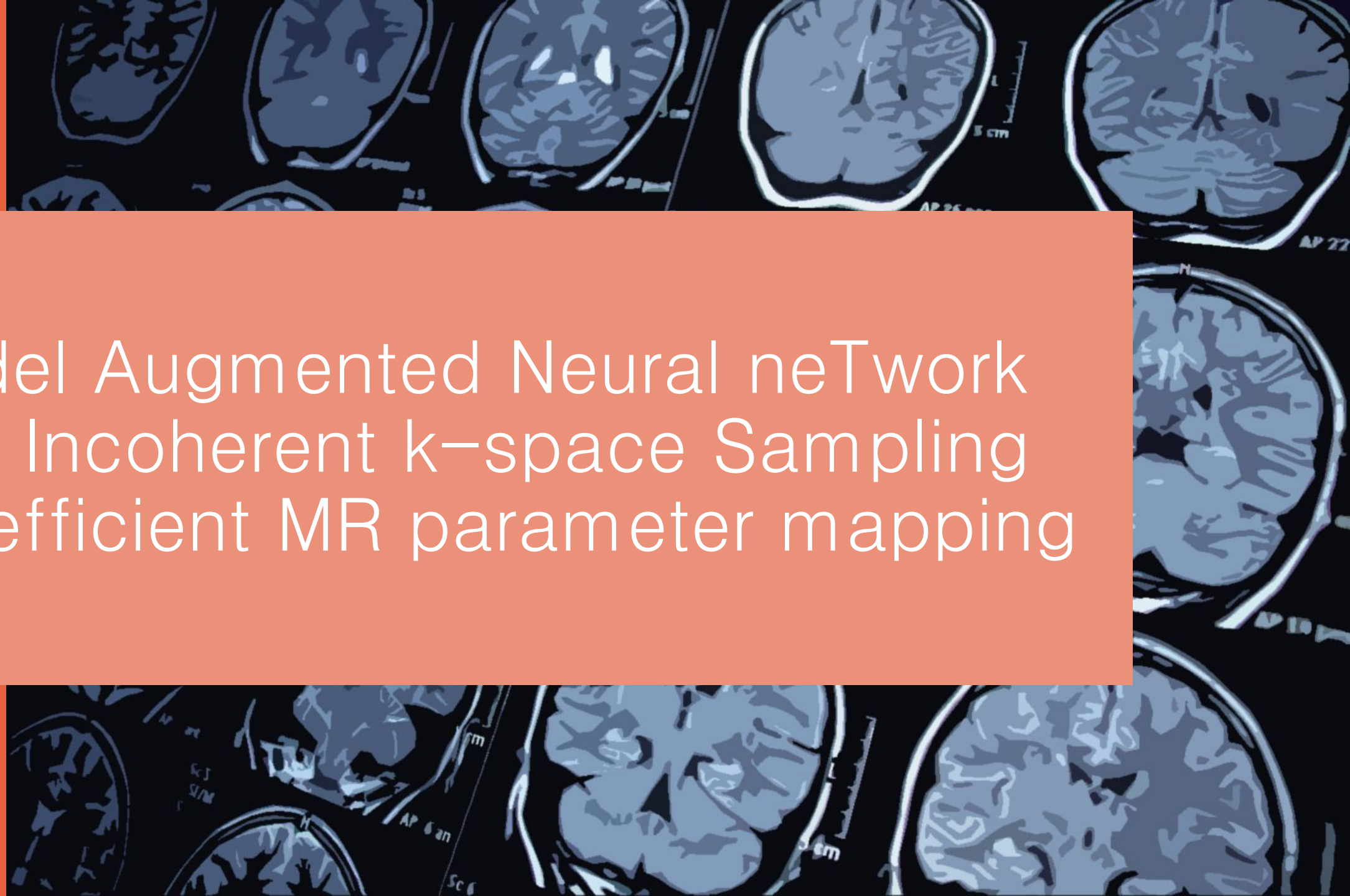
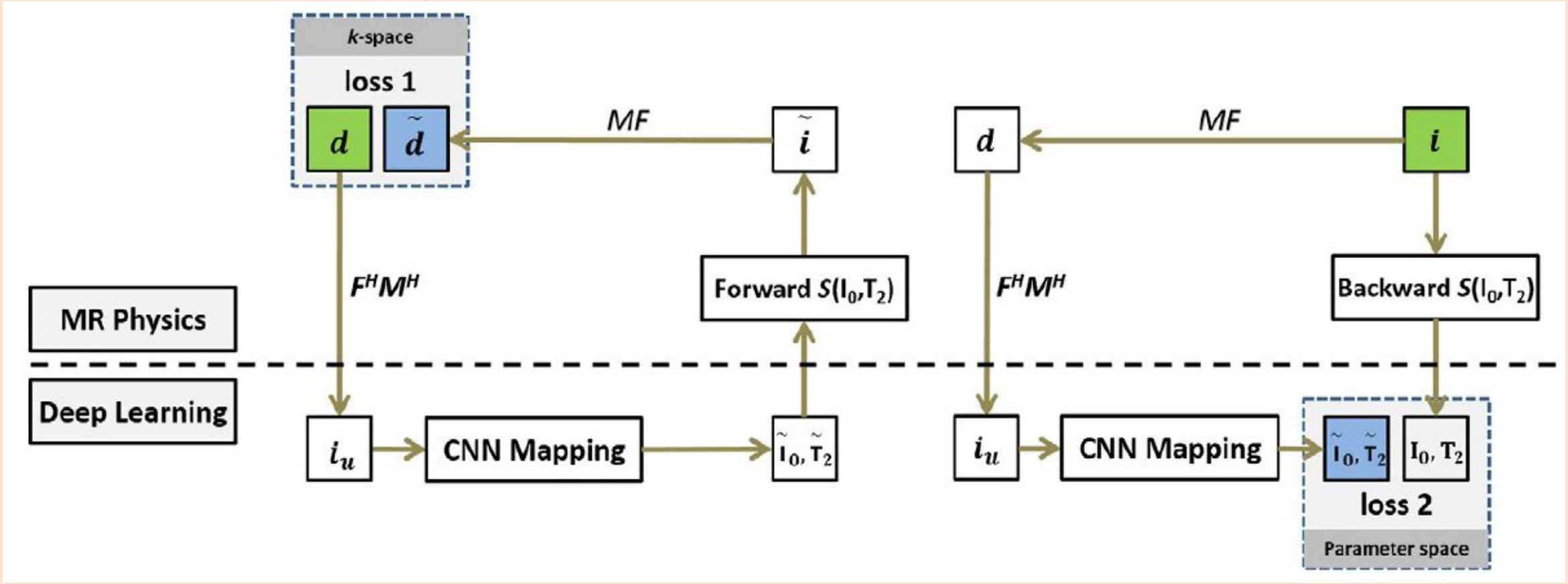


Model Augmented Neural neTwork with Incoherent k-space Sampling for efficient MR parameter mapping

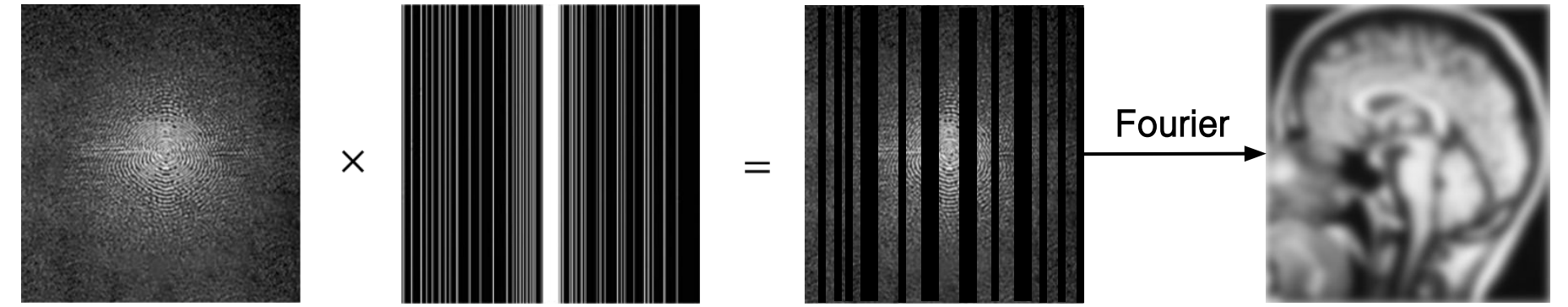
Liu et al.

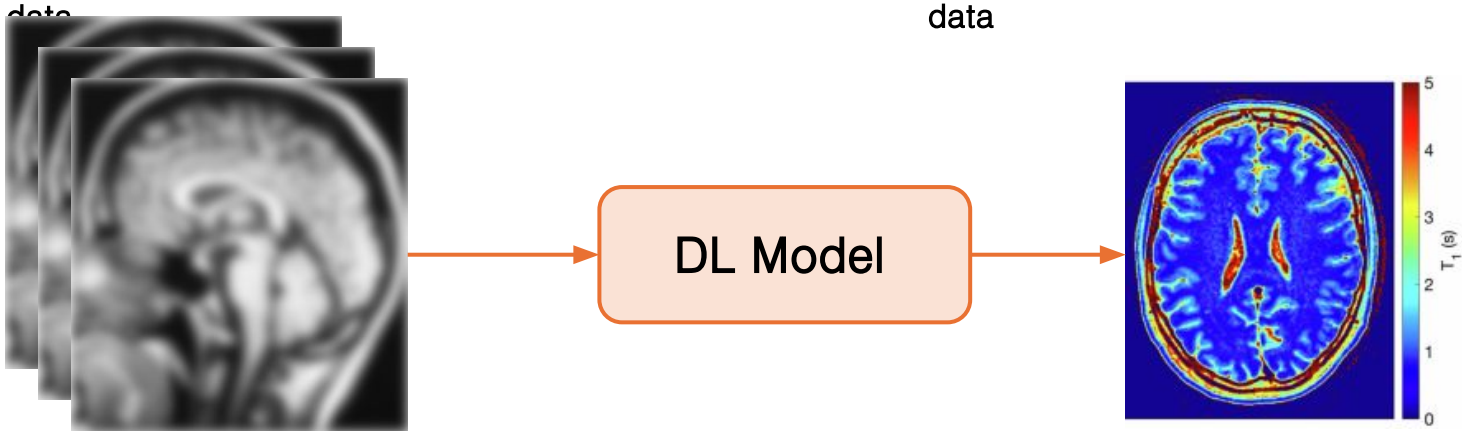
MANTIS


k-space
loss 1
d
d̃
MF
ĩ
d
MF
i
F^H M^H
Forward S(I0,T2)
F^H M^H
Backward S(I0,T2)
MR Physics
Deep Learning
iu
CNN Mapping
Ĩ0, T̃2
iu
CNN Mapping
Ĩ0, T̃2
I0, T2
loss 2
Parameter space

End-to-end CNN mapping (Learning-based)

$$R_{cnn}(I_0, T_2) = \boldsymbol{E}_{i_u \sim domain(i_u)}[\|C(i_u|\theta) - (I_0, T_2)\|_2]$$





Model-based reconstruction

$$i_j = S_j(I_0, T_2) = I_0 \cdot e^{-TE_j/T_2}$$

E: *encoding operator*

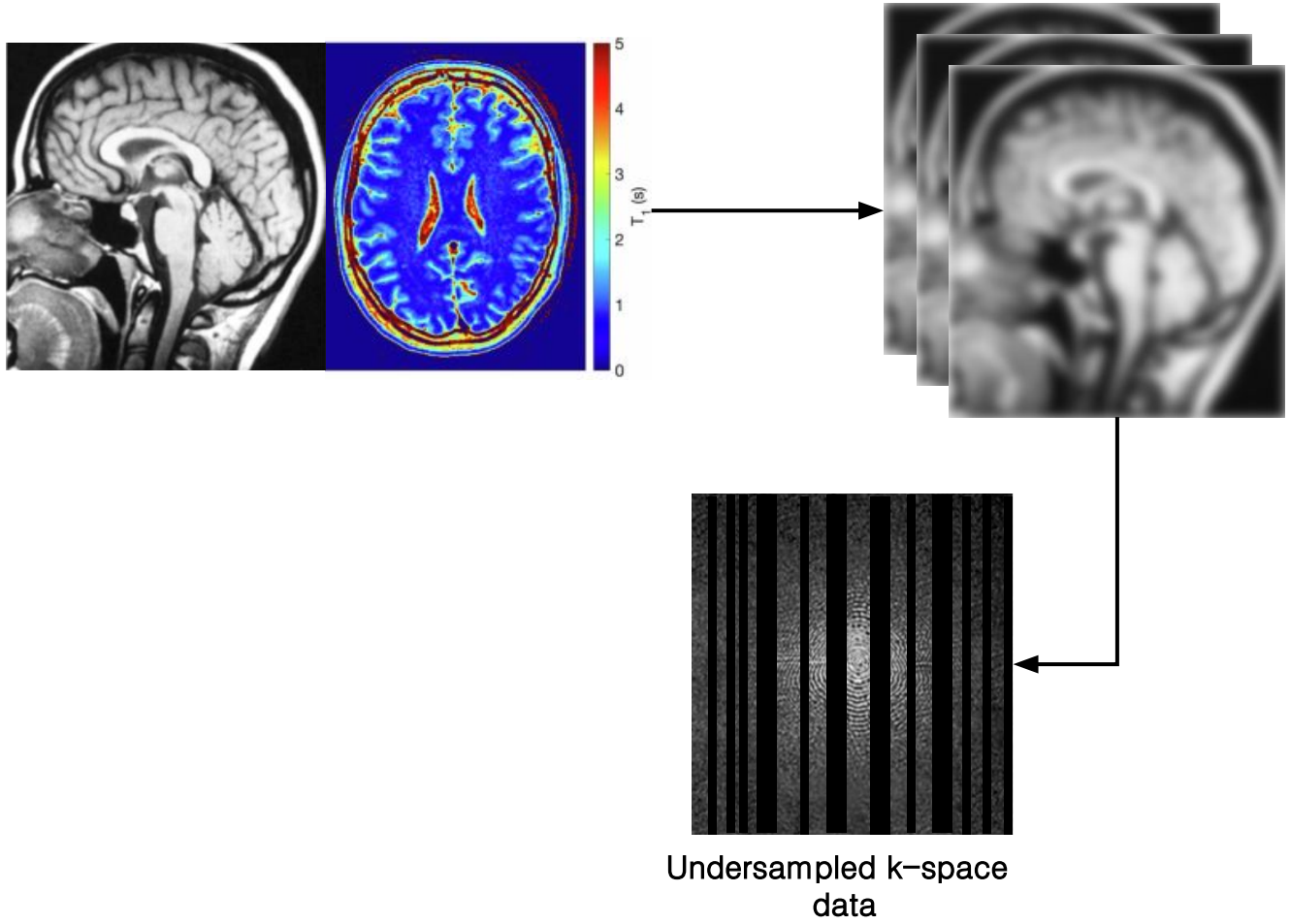
Mask

Fourier

$$d_j = Ei_j + \varepsilon$$

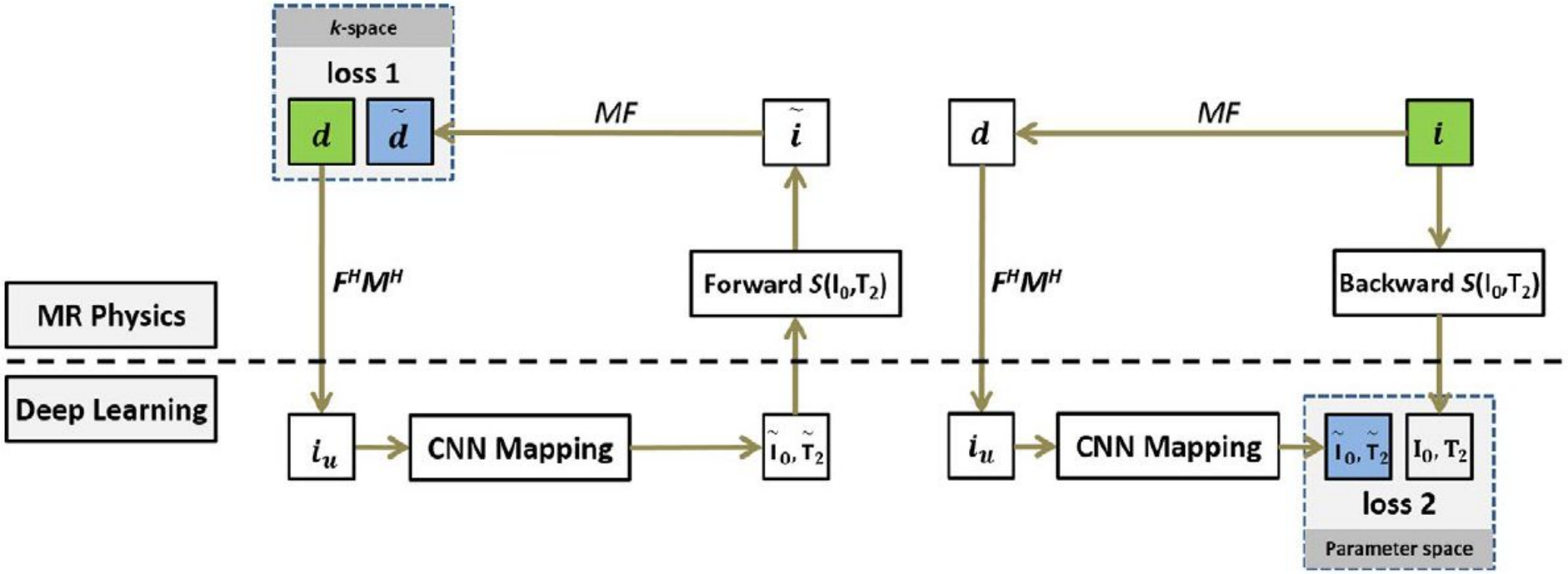
d: *k − space domain*
i: *image domain*

$$\tilde{I}_0, \tilde{T}_2 = \arg\min_{I_0, T_2} \sum_{j=1}^{t} \left\| ES_j(I_0, T_2) - d_j \right\|_2^2$$



End-to-end CNN mapping + Model consistency

$$\tilde{\theta} = \arg\min_{\theta}\left(\lambda_{data}\boldsymbol{E}_{i_u\sim domain(i_u)}\left[\sum_{j=1}^{t}\left\|ES_j\left(C(i_u|\theta)\right)-d_j\right\|_2^2\right]+\lambda_{cnn}\boldsymbol{E}_{i_u\sim domain(i_u)}[\|C(i_u|\theta)-(I_0,T_2)\|_2]\right)$$



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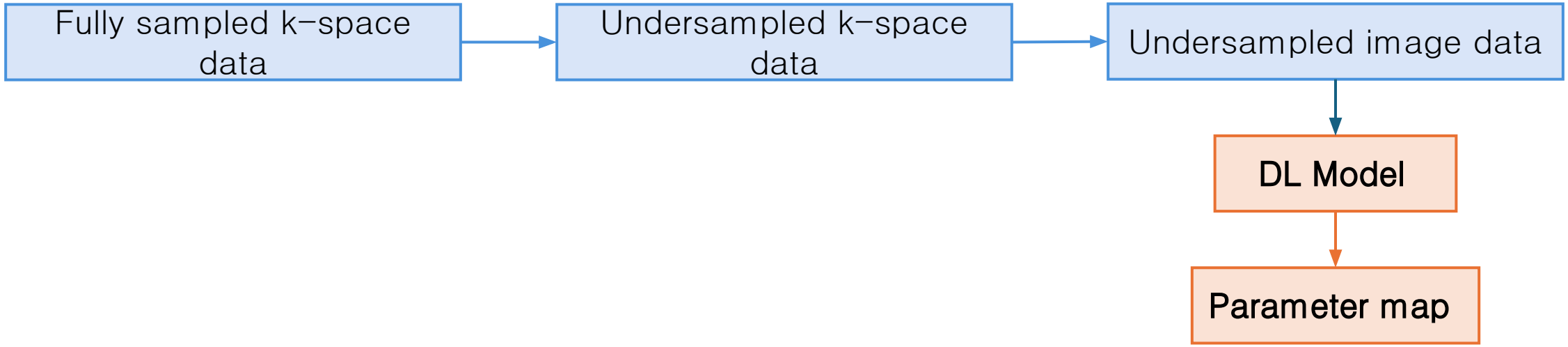

Undersampling pattern